Perceived Stress Detection through EEG Data Segmentation and Classification

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Abstract- Human stress is an increasingly prevalent and pervasive issue in modern society, posing significant challenges to individual well-being and overall societal health. There are many stressors in daily life that can trigger serious health issues, current study is focused on perceived stress. This paper aimed to investigate the correlation between electroencephalography (EEG) and Perceived Stress Scale (PSS) by utilizing data segmentation technique. The procedure involves: data acquisition, preprocessing, data segmentation, feature extraction and selection, and classification. The PSS scores were employed to record perceived stress levels of individuals. These PSS scores served as the basis for categorizing the data into two: stressed and non-stressed, and alternatively, into three classes: stressed, mildly stressed, and non-stressed. EEG recordings were captured from 40 participants (healthy and free from any known mental disorders) using 4 channel Interaxon Muse headband that was equipped with dry electrodes. The EEG data was then segmented into units of 10 seconds. The data was processed to extract five feature sets. These sets include Power Spectrum (PS), Rational Asymmetry (RASM), Differential Asymmetry (DASM), Correlation (CR) and Power Spectral Density (PSD). The stress level was accessed utilizing four classifiers: Multi-Layer Perceptron (MLP), AdaBoost M1, Random Forest and Bagging. The results indicate that AdaBoost M1 and Random Forest classifiers predicted the two classes with maximum accuracy levels of 91.52% and 88.47% for two- and three-class stress classification, respectively. These findings underline the importance of the chosen features and classifiers in increasing the prediction accuracy while contributing to the existing knowledge on stress detection with EEG signals.

Index Terms- Feature Extraction, EEG signals, Perceived Stress, Stress Detection

I. Introduction

In daily routine, there are many factors that can cause stress in human beings. Stress can be the reason of less productivity in daily tasks and in severe cases it could be life threatening [1]. Stress is the body's response to a demanding situation that can upset the equilibrium condition of the brain and is due to the physical, mental and emotional factors [2]. There are two main types of human stress: Perceived and Acute. Hard circumstances such as an unhappy marriage life, poverty, family problems and a poor career can all contribute to the perceived stress. On the other hand, Acute stress is a condition that develops quickly and usually arise due to an event like a near accident, a family argument or an expensive error at work [3]. Furthermore, significant health problems like stroke, heart attack and depression could be the result of stress. Clinical and preclinical studies of depression and perceived stress have revealed a multitude of neurochemical and morphological changes that are implicated in the pathophysiology of mood disorders. Moreover, due to complexity and heterogeneity of depression, it is challenging to pinpoint a single underlying abnormality caused by the stress [4]. The perceived level of stress can be measured subjectively using psychological questionnaires [5]. These stresses can be measured through the questionnaires created by researchers or either interview with a professional psychologist [6]. Physical and physiological techniques are also used to measure human stress levels. In physical measurements, changes could be observed in the form of eyes blink [7] and facial expression [8]. On the other hand, physiological techniques need sensors to be attached on the human body to measure changes. Stress has been measured through variety of methods including EEG [9], Heart Rate Variability (HRV) [10], Skin Conductance (SC) [11] and Heart Rate (HR) [12]. EEG is a technique that is frequently used to examine the brain activity during stressful situations [13]. Due to cost effectiveness, EEG could be preferred as a modality for monitoring the stress [14]. It is believed that the signals from EEG, ranging from 2-100 mV, can control the activity in the brain [15] and four EEG rhythms have been found to alter with the increasing levels of stress or fatigue [16]. Above 100 mV, EEG data is considered as a noise arising due to eyes movement or electrode. These noises need to be removed in order to obtain useful EEG data [17]. Four frequency bands that exist in EEG are: delta band (0.5-4 Hz), theta band (4-8 Hz), alpha band (8-13 Hz), beta band (13-30 Hz) [18]. By utilizing different number of electrodes, EEG data could be measured with the open or close eyes. Close-eye activity is simply with the participants eyes closed whereas in open-eye activity participants concentrate on a white screen [19]. The aim of the EEG-based study was to establish a link between EEG signals and PPS scores of the participants [20]. Beta bands are usually used for regression analysis to study the PSS score of individuals. High value of beta activity has been observed for perceived stress when compared with no stress conditions. In view of all this, timely coaching is required to minimize the effects of stress. In this regard, J. Bakker et al. measured physical stress symptoms utilizing sensor technology and proposed a framework for the stress management [21]. Physical symptoms of stress were observed through sensors in calendar, social media and email correspondence. The obtained results were not clear and hence, additional information was required in order to detect a significant physiological process using Galvanic Skin Response (GSR) peaks [22]. H.Jebelli et al recorded EEG data of workers in the construction sites and applied many supervised algorithms to extract time and frequency features. The best results for stress detection were achieved through Gaussian Support Vector Machine. Similar results were obtained when compared with the clinical results recorded using wired EEG devices [23]. An acquisition protocol was designed by S. A. Hosseini et al. to conduct EEG signals in picture induction environment, while using both linear and non-linear features for the extraction of EEG parameters. The classification accuracy of 82.7% was achieved with Elman classifier [24]. M. M. Sani et al. recorded EEG data from a shelter center and classified alpha band data for energy spectral density and PSD. An accuracy of 83.3% was achieved by energy spectral density with the EBF kernel function [25]. G. Jun et al. used two stressors to induce two and three level stress. While analyzing power band features of EEG data an accuracy of 75% was obtained for the three levels of stress recognition utilizing SVM classifier. Whereas, an accuracy of 96% and 88% was achieved in two level stress analysis using mental arithmetic test and Stroop color-word test respectively [26]. A. R. Subhani et al proposed a machine learning framework for the analysis of EEG signals from stressed participants. The proposed framework included EEG feature extraction, selection, classification and tenfold cross validation. The accuracies for stress identification were 94.6% and 83.4% for two level and multiple level stress respectively [27]. J. F. Alonso et. al. applied functional connectivity evaluation and univariate analysis to access the induced stress using EEG signals. An increase in beta band while decrease in high alpha band and entropy was observed [28]. EEG alpha asymmetry was also discussed for stress related disorders in the virtual environment [29]. R. Khosrowabadi et al. designed Brain Computer Interface (BCI) for classifying chronic mental stress using PSS 14. The proposed BCI showed an accuracy of 90% when the features were extracted by Magnitude Square Coherence Estimation [30]. Relationship between PSS score and closed eye resting state EEG data in perceived stress classification was studied by Saeed et al. and it was found that the beta band activity in the subjects with high stress was increased [15]. In another study, a single channel EEG headset was utilized by Saeed et al. to predict the PSS questionnaire score. By utilizing multiple linear regression, with an accuracy of 94%, this study also confirmed high beta band activity in the perceived stress [31]. Saeed et al. also proposed classification scheme for the perceived stress detection by using correlation-based feature selection method which resulted in highest correlation of beta and low gamma frequency bands with PSS score [32]. In a research conducted by Hamid et al., a significant difference in energy spectral density of alpha and beta bands, for stressed and non-stressed individuals, was found in the left and right hemispheres [33]. In order to establish a connection between EEG signals and human stress, Sulaiman et al. used alpha symmetry marker [34]. Negative correlation was observed in PSS questionnaire score and relation of alpha and beta band EEG signals in a study conducted by Hamid et al. [35]. Luijcks et. al. studied the correlation of EEG signals with EEG temporal characteristics and questionnaire score. It was found that the frontal brain has high theta band activity in post stimulus phase as compared to pre stimulus phase [36]. The classification of perceived stress by Saeed et al. contained PSS score, recorded EEG data and psychologist interview labelling which resulted in an accuracy of 85.20% [37].

Based on the available literature, the current study aims to explore the potential correlation between EEG signals and PSS scores for two and three class stress classification with a special focus on EEG data segmentation. This study diverges from the traditional methodology where a continuous (three minutes) EEG recording from each participant was captured. These (three minutes) recordings were subsequently broken down into segments of 10 seconds each. This method of data segmentation was adopted to investigate its potential impact on the overall accuracy of the stress findings. Up till now, no such specific data segmentation strategy has been reported.

II. Material and Techniques

The schematic diagram of the methodology for categorizing perceived stress utilizing EEG is given in figure 1. Four stages of capturing the EEG data such as acquisition, pre-processing, feature extraction and selection and classification are shown in the figure.

Figure 1: Block diagram illustrating the procedure for evaluating human stress using EEG

A. EEG Data Acquisition

1) Participants

Forty participants, with the age ranging from 18 to 40 years, were included in the current study. All the participants had either completed 12 years of education or university students and free from any mental disorder. The experimental study was performed according to the Helsikni declaration [38] and The University of Engineering and Technology Taxila, Pakistan approved this advanced technological progress and research study.

2) Apparatus

Interaxon Muse headband at a sampling rate of 256 Hz was used to measure the EEG signals [39]. Dry electrodes were located at positions AF7, AF8, TP9, and TP10 on a four channel headband [40]. A reference electrode was aligned at position Fpz on the participant's forehead (shown in figure 2 (b)).

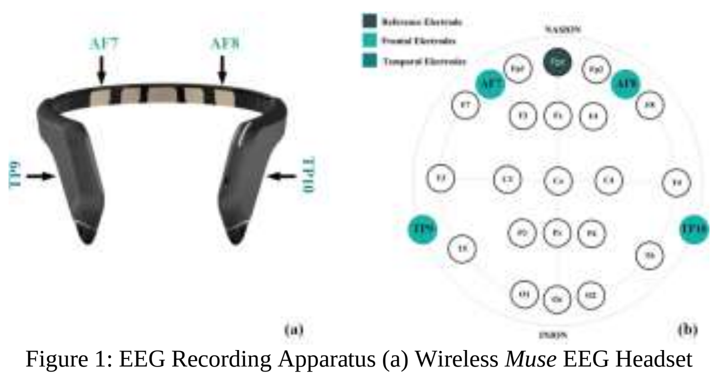

Figure 1: EEG Recording Apparatus (a) Wireless *Muse* EEG Headset (b) Electrode Positioning on Scalp

Frontal electrodes were made of silver while conductive silicon rubber was used for the temporal electrodes [41]. The recorded EEG data from the headband was transmitted to a smartphone via Bluetooth pairing, and the data was recorded on the smartphone using the Muse Monitor mobile app. Later, the data was transferred to PC for further offline processing.

3) Experimental Procedure

All the participants were guided about the experimental procedure and were made to sit in calm and temperature-controlled space with regular lighting conditions. After obtaining informed consent, the experiment commenced, and participants were initially asked to complete a demographic questionnaire (bio data sheet) which includes information about their age, gender, and history of any mental illnesses. Later, the subjects were instructed to fill PSS questionnaire to evaluate the perceived stress levels. This 10-item questionnaire calculates the amount of stress a person experienced over the last 30 days. The subjects could respond to each question on a scale from 0 to 4, with 0 for no stress experience and 4 for frequent experience over the past 30 days [42]. After gathering the questionnaire results, each subject was classified according to its obtained PSS score. In the end, EEG data was recorded for three minutes with open eyes in a relaxed position while sitting.

4) Pre-Processing

The EEG data acquired from the subjects was initially processed prior to the stage of feature extraction and categorization. An onboard DRL feedback mechanism was utilized to minimize the noise in the recorded EEG signals [43]. The purpose of DRL circuits was to ensure the good contact between EEG electrodes and the skin. A clean EEG signal can be obtained by thresholding characteristics like mean power, power standard deviation, peak amplitude, amplitude standard deviation, amplitude kurtosis, and amplitude skewness of the EEG signal [44]. However, the Muse headband had a built-in noise reduction feature which determined the EEG signal clean and ensure that the incoming signal exhibited variance, amplitude, and kurtosis values below a certain predefined threshold [45]. The frequency bands of EEG, including delta (0–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–50 Hz), were acquired through the Muse headband's internal digital signal processing unit. This processing unit applies Fast Fourier Transform to the raw EEG signals with 90% overlap on a window size of 256.

B. Feature Extraction and Selection

The interpretation of the collected EEG data involved extracting five feature sets from each frequency band for each channel, with each segment being 10 seconds long. These four features were; PS [46], RASM [47], DASM [48], CR [49] and PSD [50]. PS represents the average absolute power across four scalp electrodes in the five EEG signal frequency bands. PS consists of twenty features (five for each channel). RASM signifies the ratio of the absolute power between asymmetrical channels in the left and right brain hemispheres [51]. A total of ten RASM features, five from each band for each pair, were obtained. DASM is the disparity between the absolute power of asymmetrical channels in the left and right brain hemispheres [52]. For this, a total of ten DASM features - five from each band for each pair were attained. CR measures how two variables change with respect to each other [53]. In this reported work, CR between asymmetrical channels for the brain left and right brain hemispheres was computed. Specifically, CR between electrode pairs (TP9, TP10) and (AF7, AF8) were evaluated. This yielded a total of ten values - five from each frequency band for each pair. The PSD outlines the power spread of the signal over specific frequencies. Here, Welch method [54] was utilized to compute the PSD with 50% overlap. The mean and variance of the PSD from each band and channel were taken as features, resulting in 720 values from four channels and five bands.

Feature selection entails identifying and choosing the most pertinent and valuable features or variables from the initial data set to create a more precise and effective model [55]. The primary goal of feature selection is to remove superfluous, insignificant, or noisy features which leads to a reduction in data dimensionality. This will make an improvement in the model performance, and an increase in interpretability. In this current study, wrapper method was used for feature selection [56].

1) Wrapper Method

The wrapper method is a feature selection mechanism that 'wraps' the learning model, scrutinizing various feature assortments to find the one that enhances model performance the most [57]. The classifier is trained multiple times by utilizing feedback from each iteration to choose a subset of features for subsequent iterations. While these methods are more computationally intensive than embedded methods, they eliminate the data points that poorly discriminate between class labels when evaluated individually [58].

C. Classification

Four distinct classification algorithms were deployed to categorize perceived stress levels.

1) Multi-Layer Perceptron

A Multi-Layer Perceptron (MLP) is a type of neural network consisting of multiple layers of neurons. These layers are input, hidden, and output. The input layer receives the patterns while the output layer produces the results. Neurons in each layer are connected to the neurons in the adjacent layers with each connection having a specific weight that influences the response of neurons in the subsequent layer [59]. MLPs can virtually approximate any function with sufficient hidden units and training data hence solving the complex problems. The learning process of MLP, similar to the brain learning, involves presenting the network with a training set. This training set contain input and corresponding desired output patterns. The network starts with random connections and then refined through a process called backpropagation. This adjusts the weights based on the error between the desired and the actual outputs. This process is repeated multiple times with the same data until the connection weights are optimized. To evaluate the generalization performance of the network, it can be trained with a portion of the dataset (e.g., 80% training set) and tested with the remaining data not used for training (e.g., 20% test set) [60].

In the reported work, the learning rate for MLP was set at 0.3 which is a moderate step size for navigating the loss function's terrain. The momentum was set to 0.2. The model ran for 500 epochs while iterating through the entire dataset for each epoch. The error threshold was set at 20 and the random number generation seed was set to 0. The parameter for the number of hidden layers was automatically determined by the model.

2) Random Forest

The random forest classifier [61] employs an ensemble learning technique for the classification by utilizing multiple decision trees during the training process and producing an average prediction from the individual tree. This classifier creates forests containing random number of trees each producing unique outputs. Standard decision tree algorithms rely on a set of rules for dataset prediction and are rule-based. In contrast, random forest classifier randomly determines the root node and feature splits instead of using the gini index [62] or information gain for root node calculation. The decision process involves a majority vote, selecting the most frequently occurring class among these outputs. Consequently, the classifier's output is the class that has garnered the most votes [63].
In current study, each bag size was set to 100% of the training set size with 100 iterations indicating the number of trees in the forest. Computation was conducted sequentially with the number of execution slots set to 1. The classifier was configured to use the square root of the total number of attributes (K 0) while the minimum number of instances per leaf was set to 1.0. The variance for split calculation was assigned a value of 0.001 and the seed for the random number generator was initialized to 1.

3) Bagging

The bagging classifier algorithm is a method that utilizes various subsets of data from the datasets while dividing them into training and testing data. This algorithm generates multiple predictions or probability values which are then voted upon to derive a single real value [64]. For classification problems, the aggregation typically constitutes a majority vote. While, for the regression problems an average of predictions is taken.
In this work, bagging meta-classifier model was used, employing J48 decision trees as base classifiers. The bagging sample size was set to 100%, matching the training set size. A random seed of 1 ensured randomness in the bagging process. The execution was sequential with a single execution slot. The model performed 60 iterations, creating and training 60 separate J48 decision tree classifiers. The J48 classifier used a pruning confidence factor of 0.25, and had a minimum of 2 instances per leaf.

4) AdaBoost M1

The AdaBoost M1 algorithm is designed to optimize the classifier performance. As a member of the ensemble learning methodology family, it synergizes multiple low-performing learners into a single more accurate high-performing learner. The core concept of AdaBoost is that a weak learning algorithm, which performs marginally better than random guessing, can be transformed into an exceptionally accurate and powerful learning algorithm [65].
In current study, the AdaBoost M1 algorithm was implemented by employing J48 decision tree. The size of each bag, relative to the size of the training set, was set at 100%. The seed for random number generation was set to 1 and the number of iterations was fixed at 60. The base classifier used for boosting was the J48 decision tree with a confidence threshold for pruning set to 0.25 and a minimum number of instances per leaf was set to 2.

III. Experimental Results

A. Data Labelling

Based on their PSS scores, Participants were categorized as two-class (non-stressed and stressed) and three-class (non-stressed, mildly stressed, and stressed) stress classification (shown in figure 3).

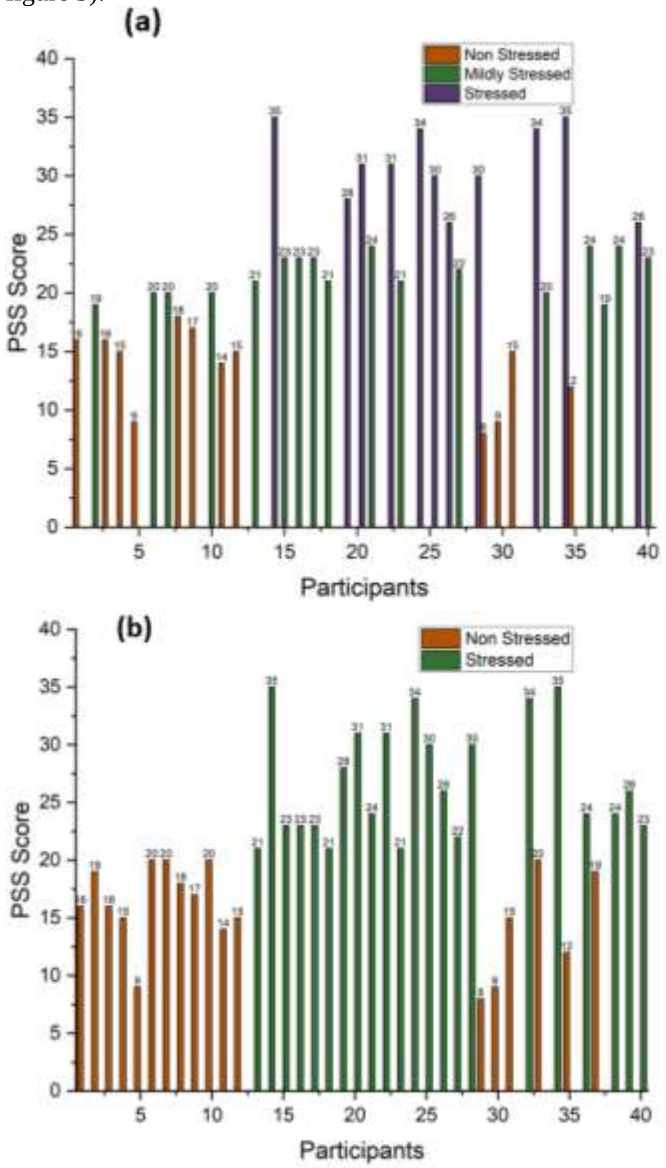

Figure 3: Distribution of Participants based on PSS score for (a) two- and (b) three-class stress classification

The PSS scores of 40 participants yielded a mean (μPSS) of 21.8 and a standard deviation (σPSS) of 7.15. In the case of two-class stress classification, participants with PSS scores ranging from 0 to 20 were labeled as non-stressed while those scoring between 21 and 40 were identified as stressed. This classification resulted in 22 subjects being marked as stressed with the remaining 18 subjects falling in the non-stressed category. In the three-class stress classification, participants were divided into three groups based on the specific ranges of PSS scores. Subjects with a PSS score between 0 and (μPSS - σPSS/2) were labeled as non-stressed, those with a PSS score between (μPSS - σPSS/2) + 1 and (μPSS + σPSS/2) - 1 were labeled as mildly stressed and those with a PSS score ranging from (μPSS + σPSS/2) up to 40 were identified as stressed. Following this scheme, 12 participants were labeled non-stressed, 17 were mildly stressed, and 11 were identified as stressed.

B. Performance Analysis

1) Two-Class Stress Classification

The MLP model achieved an overall accuracy of 90.28% by correctly classifying 650 instances. The calculated kappa statistic was 0.8033 which signified the strong agreement between the model's predictions and the actual classes. The Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) were relatively low 0.1109 and 0.2892 respectively, indicating the model's predictions were relatively close to the actual values. The Relative Absolute Error (RAE) and the Root Relative Square Error (RRSE), measures of the model's prediction errors in relation to a simple predictor, were 22.41% and 58.13% respectively. Looking at the class-specific metrics, the model demonstrated slightly better performance on the "stressed" class, with a higher True Positive (TP) rate of 0.919 when compared to 0.883 for the "non-stressed" class. This indicates that the model was somewhat more effective at correctly identifying "stressed" instances. Both classes had high F-measures (0.912 for "stressed" and 0.891 for "non-stressed") indicating good balance between precision and recall. The Matthews Correlation Coefficient (MCC) values came out to be 0.803 for both classes, suggesting that the binary classifications are highly correlated with the observed outcomes. The Receiver Operating Characteristic (ROC) area and Precision Recall Curve (PRC) area were above 0.9 for both classes implying that the model has a strong discriminative capacity between classes and a high precision-recall trade-off. The confusion matrix confirmed the model's superior ability to correctly identify "stressed" instances (364 correct predictions out of 396 actual instances) compared to "non-stressed" instances (286 correct predictions out of 324 actual instances). It was observed that the misclassifications, "non-stressed" class being classified as "stressed" were more prominent [66].

The bagging model demonstrated better performance, correctly classifying 644 instances, with an overall classification accuracy of 89.44%. However, the model exhibited MAE of 0.2491 and RMSE of 0.3218. The RAE and the RRSE are 50.33% and 64.69% respectively, indicating that the model predictions have relatively higher errors. The class-specific metrics showed that the model had a slightly higher TP rate of 0.919 for the "stressed" class compared to 0.864 for the "non-tressed" class. This suggested that the model was better at correctly identifying "stressed" instances. The precision was also high for both classes (0.897 for "non-stressed" and 0.892 for "stressed"). Thus, indicating a strong performance in terms of the proportion of TP identifications from all positive predictions. The MCC values were 0.786 for both classes, suggesting a substantial correlation between the observed and predicted binary classifications. The ROC area for both classes was 0.937 indicating high TP rate and a low false positive (FP) rate. The PRC area was also high for both classes. In the confusion matrix, the model made more correct predictions for the "stressed" class (364 out of 396 actual instances) compared to the "non-stressed" class (280 out of 324 actual instances). However, most misclassification came from the "non-stressed" class which was incorrectly predicted as "stressed".

The Random Forest model achieved an overall accuracy of 89.58% correctly classifying 645 instances with misclassification rate of 10.42%. The kappa statistic of 0.789 signified substantial agreement between the model's predictions and the actual classes. Examining the detailed accuracy by class, the model achieved a TP rate of 86.7% for "non-tressed" and 91.9% for "stressed". Meanwhile, the FP rate was relatively low 8.1% for "non-tressed" and 13.3% for "stressed". The F-Measure was 0.882 for "non-tressed" and 0.907 for "stressed". These high values suggested that the model performed well in terms of both retrieving relevant instances (recall) and the proportion of correct positive predictions (precision). However, the MAE and RMSE were relatively high, 0.2592 and 0.3173 respectively. The confusion matrix provided further support for these findings, the model correctly classified 281 as "non- stressed" and misclassified 43 instances as "stressed". In the "stressed" category, the model correctly identified 364 instances while incorrectly labeled 32 instances as "non-stressed". The MCC also suggested a strong performance, with a score of 0.789, indicating a high degree of correlation between the observed and predicted binary classifications.

(a)

NS	S	← Classified as
286	38	NS
32	364	S

(b)

NS	S	← Classified as
281	43	NS
32	364	S

(c)

NS	S	← Classified as
280	44	NS
32	364	S

(d)

NS	S	← Classified as
287	37	NS
24	372	S

Figure 4: Confusion Matrices for (a) Multi-Layer perceptron, (b) Random Forest, (c) Bagging, and (d) AdaBoost classifier for two class classification (where, NS=Non Stressed & S=Stressed).

The AdaBoost M1 model results indicated a strong performance with an overall accuracy of 91.53%. The kappa statistic was 0.8282. Examining the detailed accuracy by class, the model showed slightly better performance on "stressed" instances with a TP rate of 0.939 compared to the "non-stressed" instances with a TP rate of 0.886. In addition, the model demonstrated strong precision, recall, and F-measure scores for both classes hence reinforcing its effective predictive capacity. The confusion matrix further elaborated on the performance, where the model classified 287 out of 324 instances correctly as "no-stressed" and misclassified 37 instances. For the "stressed" class, the model performed even better by correctly classifying 372 out of 396 instances and incorrectly classifying 24. The relatively higher TP rate and lower FP rate for the "stressed" class suggest that the model was more adept at identifying "stressed" instances compared to the "non-stressed". These results overall indicated a robust classification capability of the AdaBoost M1 model in this scenario.

2) Three-Class Stress Classifications

The bagging classifier demonstrated an overall classification accuracy of 81.9444%. The model's kappa statistic was 0.7237, representing a substantial level of agreement between the predictions and the actual classes. The MAE value was 0.2315, and the RMSE 0.3117. However, the RAE of 53.0998% and the RRSE of 66.7704% indicated a fair degree of prediction error compared to a naive baseline model. In terms of class-specific accuracy, highest TP rate for the "mildly stressed" class (0.833), followed by "non- stressed" (0.824), and "stressed" (0.793) was observed. The FP rate was highest for the "mildly stressed" class (0.126). Precision was relatively well-balanced across the classes. The model achieved F-Measure scores between 0.803 and 0.832 across all the classes, suggesting a fairly balanced model performance. The MCC scores ranging from 0.707 to 0.737 also indicated a good correlation between predictions and the actual classes. The ROC area was above 0.9 for all the classes. Similarly, the PRC area was high across all the classes. The confusion matrix revealed that the model performed best in classifying "non-stressed" instances correctly (178 correct predictions) and struggled the most with "mildly stressed" instances (255 correct predictions).

(a)

NS	MS	S	← Classified as
164	37	15	NS
16	270	20	MS
15	27	156	S

(b)

NS	MS	S	← Classified as
182	25	9	NS
10	286	10	MS
7	22	169	S

(c)

NS	MS	S	← Classified as
178	25	13	NS
28	255	23	MS
14	27	157	S

(d)

NS	MS	S	← Classified as
187	19	10	NS
17	277	12	MS
4	22	172	S

Figure 5: Confusion Matrices for (a) Multi-layer Perceptron, (b) Random Forest, (c) Bagging, and (d) AdaBoost classifier for two class classification (where, NS=Non Stressed, MS=Mildly Stressed & S=Stressed).

The AdaBoost M1 model exhibited a strong overall classification accuracy of 88.3333%, correctly classifying 636 instances. The kappa statistic for this model was 0.8209. This suggested that the model's predictions were reliable and not simply due to chance. The MAE and the RMSE were fairly low at 0.0792 and 0.2756 respectively, indicating that the model's predictions were quite close to the actual values. The RAE of 18.1801% and the RRSE of 59.0315% both highlighted that the model's prediction errors were significantly lower than a simple predictor, reinforcing the model's superior performance. In terms of class-specific metrics, this model demonstrated high performance across all classes, with TP rates above 0.86 for all the classes. The model was particularly adept at identifying the "mildly stressed" class, with the TP rate of 0.905. The FP rates were low across the board, indicating that the model seldom misclassified instances into the wrong class. The F-measure showed high values for all the classes, ranging from 0.878 to 0.888, suggesting good balance between precision and recall. MCC was above 0.8 for all the classes. The model exhibited strong discriminative capacity as suggested by ROC area values above 0.96 for all the classes. Likewise, the PRC area values reflected the trade-off between precision and recall signifying that the model maintained a strong balance between these two metrics. The confusion matrix demonstrated that the model performed best in identifying "non-stressed" instances (187 correct predictions) and least adept in correctly identifying the "stressed" instances (172 correct predictions). Misclassifications were primarily between "non-stressed" and "mildly stressed" classes, and also between "stressed" and "mildly stressed" classes.

The Random Forest model correctly classified 637 instances, equating to an overall accuracy of 88.4722%. This superior performance is reinforced by the kappa statistic of 0.8223. Despite its strong classification performance, the model exhibited a relatively high MAE of 0.2472 and RMSE of 0.305. The RAE and the RRSE were 56.7049% and 65.33% respectively. Class-specific performance of the model was also remarkable, with the "mildly stressed" class experiencing the highest TP Rate at 0.935. Both "non-stressed" and "Stressed" classes had TP rates above 0.84. FP rates were minimal for all classes, indicating that the model did not misclassified instances frequently. The model's precision, recall, F-Measure, and MCC all exhibited high values and hence suggested that the model's predictions were reliable across all the classes. Furthermore, all classes had ROC area values above 0.958 which signified excellent class discrimination capabilities. Likewise, high PRC area values attested the model's solid performance in balancing precision and recall. The confusion matrix reveals that most misclassifications occurred between the "non-stressed" and "mildly stressed" classes, as well as between the "stressed" and "mildly stressed" classes. Overall, the Random Forest model exhibited robust performance in classifying instances into all three categories.

IV. Discussion

The obtained results had shown varying levels of accuracy with different classifiers. While, a comparison with literature revealed a rich blend of methodologies, models, and features employed by various researchers in the past. For the two-class stress classifier system, the current study used MLP, bagging, Random Forest, and AdaBoost M1. Among these, AdaBoost yielded the highest accuracy with 91.52% correct classification instances followed closely by MLP. However, from literature it was revealed that a range of other classifiers were also used. For example, C.K. Alfred & C. Chia employed Linear Discriminant Analysis (LDA), K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN) classifiers and achieved a maximum classification rate of 72% through KNN with Discrete Cosine Transform (DCT) [67]. Likewise, Saeed et. al. utilized the Naive Bayes algorithm and achieved an accuracy of 71.4% in stress level classification [31].

In the three-class classifier system, the Random Forest and AdaBoost classifiers achieved relatively high accuracy rates of 88.4722% and 88.3333% respectively. Whereas, Arsalan et al managed to achieve 64.28% accuracy for three-class classifications utilizing similar set of classifiers and highlighting the potential variability in performance across different datasets and stress detection approaches [20]. Saeed et al. demonstrated that correlation-based feature subset selection techniques combined with neural oscillations improved the stress classification accuracy to 78.57% [32]. These findings closely align with the AdaBoost findings for the 3-class classifier in the current study. Similarly, Jebelli et al. reported an accuracy of 71.1% by utilizing support vector machine learning algorithm

[68] which again mirrors the findings of the present study. Nagar & Sethia also corroborated the results of the current study by highlighting the effectiveness of the KNN algorithm in classifying stress with 74.43% average classification accuracy [69]. Arsalan et al. reported 75% accuracy rate with MLP classifier [70]. This accuracy rate is slightly lower than the corresponding results in the present study.

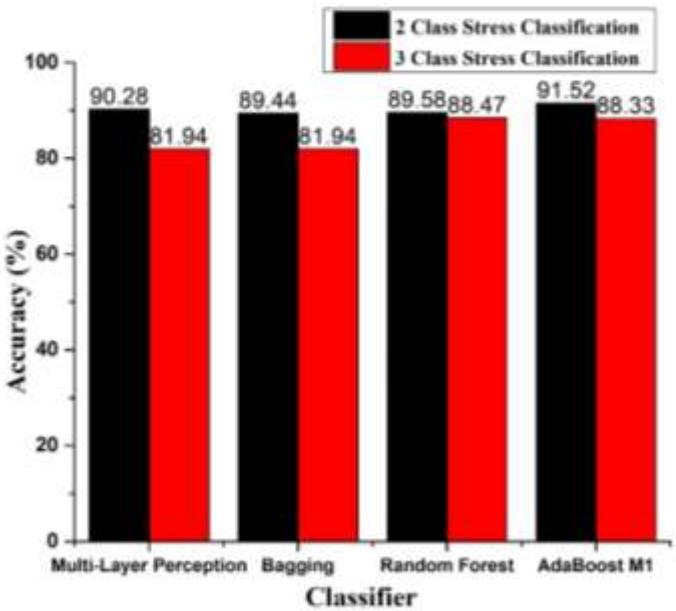

Figure 6: Accuracy achieved for two- and three-class stress classification using the Multi-Layer Perceptron, Bagging, Random Forest, and AdaBoost M1 classifiers.

Previous studies have shown that the stress detection utilizing EEG signals is feasible and effective. A. Hamid et al. and Hambali et al. found correlations between EEG signals and stress levels as measured by the PSS [35], [71]. Similar to this, the findings from the current study stand comparatively well against the findings from the literature for both two- and three-class stress classification. Nevertheless, some studies exhibited even higher accuracy levels as Saeed et al achieved stress classification accuracy of 85.20% through Support Vector Machines and alpha asymmetry [72]. In terms of features, the current study leveraged a varying number of attributes for different classifiers. These attributes consisting of several distinct features ranging from 20 to 30 in the two-class stress classifier system and from 14 to 28 in the three-class stress classifier system. Whereas, other studies had explored the use of various distinctive features such as alpha and beta asymmetries [72], low beta waves [31], or EEG-based connectivity patterns [73]. It should be noted that while the results of the present study are promising, the literature survey revealed a myriad of methodologies employed for stress detection. Each study targeted a different aspect of stress and leveraged different features, classifiers, or number of attributes. The differences in the obtained results highlight the importance of considering factors such as diversity of the study population, types of stressors used, choice of classifier, and features selected.

V. Conclusion

An analytical investigation has been conducted with the main objective to classify Stress Levels in individuals. The study primarily focused on binary and multiclass stress classification using Power Spectrum, Rational Asymmetry, Differential Asymmetry, Correlation and Power Spectral Density features extracted from the Alpha, Beta, Gamma, Delta, and Theta bands of EEG signals. These features were extracted from EEG data segments with a duration of 10 seconds. A wrapper method was used to select the features that contributed the most to the classification accuracy. The selected features were then utilized as input for four classifiers: Multi-Layer Perceptron, Bagging, Random Forest, and AdaBoost M1. It was noted that the findings highlighted the effectiveness of AdaBoost M1 and Random Forest classifiers in predicting the classes, obtaining maximum accuracy of 91.52% and 88.47% respectively for two and three class stress classification. In future, our aim is to classify stress levels for four-class classification.

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